A Personality-Based Model of Emotional Contagion and Control in Crowd Queuing Simulations

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Queuing is a frequent daily activity. However, long waiting lines equate to frustration and potential safety hazards. We present a novel, personality-based model of emotional contagion and control for simulating crowd queuing. Our model integrates the influence of individual personalities and interpersonal relationships. Through the interaction between the agents and the external environment parameters, the emotional contagion model based on well-known theories in psychology is used to complete the agents' behaviour planning and path planning function. We combine the epidemiological SIR model with the cellular automaton model to capture various emotional modelling for multi-agent simulations. The overall formulation involves different emotional parameters, such as patience, urgency, and friendliness, closely related to crowd queuing. In addition, to manage the order of the queue, governing agents are added to prevent the emotional outbreak. We perform qualitative and quantitative comparisons between our simulation results and real-world observations on various scenarios. Numerous experiments show that reasonably increasing the queue channel and adding governing agents can effectively improve the quality of queues.

CCS Concepts: • **Computing methodologies** → *Modeling and simulation*.

Additional Key Words and Phrases: crowd simulation, emotional contagion, queue management

1 INTRODUCTION

With the explosive growth of urban populations [14], researching behaviour simulations of crowd queuing is of increasing practical significance. Using dynamic crowd simulations for queuing events can help managers scientifically and effectively improve queuing management and service quality on queuing system capacity, service windows numbers, and service levels. At the same time, once panic situations occur, emotional changes among individuals can affect the development of events. It is essential to understand the psychological behaviours of crowds during queuing events and potentially use those techniques to manage crowds. The typical queue management techniques include the proper queue structure [47], distinguishing different waiting crowds [42], and reducing the waiting time in the crowd feeling [39].

People often encounter queuing scenes as they go about daily activities, such as moving in hospitals, waiting for service at the bank window, waiting for the bus, and so on. With the rapid growth of urban populations, the difficulty of public management and public services increases in queuing behaviours, and so do the security

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risks caused by crowds. The uncivilized behaviour of some individuals while forming queues may lead to serious group incidents. In his book *The Crowd: A Study of The Popular Mind* [36], Gustave Le Bon pointed out that the mutual infection of group emotions determines group behaviour; instinctive emotions are especially susceptible to infection, while rational and calm emotions do not work in the group. On December 31, 2014, severe crowd and stampede incidents occurred in Shanghai's Bund. At that time, nearly 300,000 citizens and tourists flocked to the Bund's viewing platform. Because some individuals rushing to the viewing platform went through the pedestrian walkway the wrong way, they broke through the one-way traffic warning zone. Due to the lack of police officers, the situation became out of control. Crowding and stampeding occurred, causing the deaths of 35 people.

Queuing is a common daily activity. Having customers waiting in line is instinctively a good sign for business. However, long waiting lines cause frustration and waste of time. In many retail stores and banks, management routinely uses queueing models to help manage and allocate resources to respond to demands quickly and cost-efficiently [13, 25]. In queuing events, individuals' emotions infect each other, and the behavioural characteristics of the crowd are different from normal crowd movement. It is helpful to explore and analyze the crowd's psychological and emotional infection patterns and formulate a scientific crowd queuing management plan to improve the quality of queuing services and avoid the risks of congestion accidents. These outcomes have important practical significance for building a harmonious society.

The biggest challenge is analyzing the crowd's social group and behavioural characteristics. Social group members have specific social relationships, consistent consciousness and norms, consistent ability to act, and certain group boundaries [23]. At the same time, behavioural characteristics refer to the actual behaviour of the crowd. Individuals' behaviours are dominated by their characteristics and factors in the surrounding environment [33]. These factors are usually generated by Local Rules [43], Forces [27], and Flows [12] in the virtual animation of the simulated crowd. Other challenges in analyzing crowd emotion infections are producing individual behaviours through individual communications and modelling how the psychological model enhances real-time behaviours [50]. The current state of the research lacks a reasonable and practical emotional infection model to build a crowd queuing model.

Using psychology and social computing, we study the problem of emotional infection in crowds involved in queuing events and establish an emotional infection model based on patience [41], urgency [20], and friendship [51], which effectively characterize individual personality and emotion. Based on the extension of the model proposed by Fu et al. [21], we simulate the dynamic behaviour of queuing crowds by adding personality and emotional parameters to the classical SIR model [31]. Each individual may produce different emotions and behaviours when panic situations occur [45]. To verify the proposed model, we choose five typical scenes to simulate the dynamic trend of crowd queuing events: the ATM, the subway station, the bus station, indoor service windows with isolation barriers, and outdoor service windows without isolation barriers. Experiments show that the proposed model can realistically simulate crowd queuing movements in various scenarios.

To effectively control crowd disruption, we added governing agents to the proposed model of emotional contagion [64]. The governing agent is equivalent to a positive emotion source that inhibits the propagation of negative emotions and plays a role in maintaining order in the queue. In the experiments, we use the subway scene to simulate the crowd movement in the queues under the administrators' management. Our experimental results show that adding the administrator at the right time can effectively prevent crowd confusion.

First, some related works are reviewed in Section 2, followed by a detailed statement of emotional contagion and control modelling in Section 3. Then we present a method for agent behaviour modelling in Section 4. We present experimental results for queuing scenarios in Section 5. In Section 6, we analyze and discuss the experimental results. Finally, Section 7 gives conclusions and future work.

2 RELATES WORKS

2.1 Crowd simulation methodologies

Many researchers have proposed different kinds of models to perform crowd simulation under general cases: cellular automatons [8], social forces [27], continuum flow [53], agent-based [55], data-driven [38], geometrical [26], synthetic vision-based [44], particle-based [28], and OCEAN models [17]. Yang et al. [61] review crowd simulation models from traditional to current methods (group simulation, emotion contagion). Brogan and Hodgins [6] model the motion of crows with a physical machine using particle systems. Helbing et al. [27] present a method to simulate the motion of pedestrians based on the social force model, a microscopic (personal) method for pedestrian motion simulation. It solves Newton's equation for each individual and considers repulsive interactions, friction forces, dissipation, and fluctuations. Funge et al. [22] devote themselves to creating artificial life for behavioural animation. This method can endow virtual agents with comprehensive visual and environmental perception abilities. Xu et al. [58] work on applying crowd simulation to crowd formation transforms to achieve transition and control of the visual pleasure of the crowd. Yao et al. [63] present a residual network-based scene-independent crowd simulation (ResNet-SICS) framework to simulate crowd motion. Dickinson et al. [15] create a simulation in which participants walk freely and perform a routine manual task while interacting with agents controlled by a typical social force simulation model. Li et al. [37] present an antagonistic crowd simulation model, ACSEE, integrated with antagonistic emotional contagion and evolutionary game theories. Toll et al. [54] present a novel framework that generously describes local agent navigation as optimizing a cost function in velocity space. Bode [3] proposes an alternative pedestrian model calibration approach using Approximate Bayesian Computation (ABC). Fraichard et al. [19] present the result of a study aiming to investigate to what extent the results obtained in the crowd simulation domain could be used to control a mobile robot navigating among people. Lim et al. [40] use the phase-by-phase methodology to investigate crowd simulations in digital cultural heritage, which focus on ethnic groups with heterogeneous behaviors. Basak et al. [2] propose a data-driven approach to tune, validate, and optimize crowd simulations by learning parameters from real videos.

Social force and cellular automaton models are widely used in crowd simulation [11, 32, 52]. The difference between them is the discretization of time and space. Social force models are continuous microscopical models. In these models, individuals' social behaviour is used to induce changes in the social domain of individuals to describe the behaviour of the crowd. Unlike the general dynamic models, the cellular automaton models are not determined by strictly defined physical equations or functions but by rules calculated according to their previous states and the states of adjacent cells [34].

2.2 Emotional contagion models

Various emotion models have been established to simulate an agent by giving the agent emotional parameters, such as the agent emotional model-based OCC [62]. In real scenarios, emotional contagion is a natural phenomenon in crowds, and people's emotions can affect their behavior [59]. Compared with the traditional crowd models without emotions, the models with agent emotions modelling is more realistic in analyzing human behavior and are more valuable. Related research has quantified the impact of social-psychological factors on available models and has achieved a certain degree of success. Based on the emotional contagion theory in social psychology, Bosse proposes a model based on emotional interaction [4]. Durupinar observes and studies how individuals with different personalities interact in the OCEAN model by changing their parameters, and personality affects individual perception and behaviour. Hong et al. propose [29] a personalized virtual and physical cyberspace-based emotional contagion model (PVP-ECM) to simulate the process of crowd emotional contagion. The results show that individual behaviour relates to the external environment and personality [17].

2.3 Crowd simulation with emotional contagion

Recently, researchers have developed a variety of crowd simulation methods. However, most methods focus on how people plan paths [30] or solve the problem of obstacle avoidance in high-density crowds [35]. Some researchers study the interaction between people using the social force model [46], which is particularly useful in the study of crowd evacuation [21]. Other researchers study social interaction, such as emotional transmission [9, 10]. Peter M. Sandman [48] tries to combine emotion with behaviour, but no theoretical derivation of the emotion-behavior link was made, and no relevant simulation experimental results and analysis were given. Xue et al. [60] propose an emotional contagion method that combines an improved SIR model with a cellular automaton model.

These studies support the notion that the emotions of queuing crowds are mutually contagious and greatly influence queuing order. Therefore, a critical theme of crowd queuing simulation is the analysis of emotional infections within a crowd and how the psychological model enhances the real-time behaviour of individuals. In addition, crowding accidents can quickly occur among individuals when negative emotional contagion occurs due to queue jumping. The most basic method to prevent crowd chaos is assigning administrators to manage queuing order and comfort crowds [7]. Therefore, the analysis of control mechanisms is another important theme for crowd queuing simulations. We have briefly studied the problem of emotional contagion in crowd queueing [60]. In contrast to the current results, we attempt to further establish a unified model with emotional contagion and control mechanisms for crowd queuing simulations from psychology and social computing. We will particularly study how to increase the positive emotional source of queuing crowds by using administrators to keep the emotions of the queuing crowd stable.

3 MODELING EMOTIONAL CONTAGION AND CONTROL

In psychology, individual sentiment is usually divided into personality and emotion. Personality refers to the unique and stable psychological characteristics of different individuals, which is a stable trait formed by the long-term habits of an individual. Emotion is a constantly changing and unstable psychological feature affected by goals, standards, and attitudes. Personality and emotion work together to drive individuals' behaviours.

Recently, researchers have formed a relatively consistent consensus on personality description. A lexicographical approach found about five characteristics to cover all aspects of personality description, called the Five-Factor Model(OCEAN model), divides personality into five categories: openness, conscientiousness, extraversion, agreeableness, and neuroticism [24]. The OCEAN model focuses on the appearance of individuals with different personality characteristics and does not further explain the link between the five characteristic dimensions and behavior. Durupinar researched how individuals with different personalities interact in the OCEAN model by changing their parameters and how personality affects individuals' perceptions and behaviors [17]. Durupinar's results provided a significant reference for later simulations of crowd behavior. In this paper, we also enrich the emotional contagion model by adding individual personality parameters to make the simulation results more realistic.

The individual personality is extremely difficult to change and spread, but individual emotions are contagious and influenced by the environment. Individual emotions are differentiated, and different environments produce emotions such as interest, pleasure, surprise, sadness, anger, disgust, contempt, fear, shyness, and timidity [1]. Considering an individual's all emotions is hugely challenging for the construction and computation of the model. Our model is based on individual emotion contagion, so we divided individual emotions into two major types to facilitate model construction and computation. Two kinds of emotional value parameters (e_{neg}, e_{pos}) are involved in representing these two states, and they satisfy the following relationships [5]:

$$\begin{cases} 0.5 \leq e_{pos} \leq 1, \\ 0 \leq e_{neg} < 0.5, \\ e_{pos} + e_{neg} = 1. \end{cases} \tag{1}$$

Equation (1) begins with the sum of each agent's positive and negative emotional values equal 1. The closer the emotional value is to 1, the higher the positive degree of the agent. On the contrary, if the emotional value is closer to 0, the higher the negative degree of the agent, the greater the possibility of queue-jumping behaviour.

3.1 Self factors impact on emotional value

Individuals in queuing scenarios are often prone to be queue jumpers due to factors such as when they are in a hurry to obtain service access, wait too long, or have short patience. The negative emotional value of individuals is highly correlated with their factors.

Based on the existing research on personality characteristics, we combined it with the queuing scenario of this study. Three personality parameters are proposed for queuing models: ω_i(patience) [41], u_i(urgency) [20], and f_i(friendliness) [51]. The following explains and details the relationship between the three proposed personality parameters and individuals.

- ω_i indicates the time that an individual i is willing to wait in the queue; the greater its value, the more patient the individual is. Mandelbaum and Zeltyn [41] show that the probability of an individual giving up on waiting has a specific relationship with the average waiting time (patience). However, different individuals have different degrees of patience and are willing to wait for different times. Therefore, in our experiments, we randomly assign the patience value of the agents and use it as a constant attribute of the individuals.
- u_i indicates the urgency of receiving the service. Kenneth [20] indicates that due to an increase in psychological pressure, such as time urgency, within a specific range, the ability of individuals to solve the situation will decrease. We derive this intrinsic factor for queuing scenarios as urgency, which indicates the urgency with individuals wishing to receive the service, affecting individual behaviors such as queue jumping.
- f_i indicates the friendliness of an individual. The bigger the value, the friendlier the person. Smits and Cherhoniak [51] believe that the higher the degree of friendliness, the greater the attractiveness of an individual, so the queue jumper is more willing to jump the queue in front of these friendlier individuals. The factor is proposed to calculate the position of the queue jumper to jump the queue.

We analyze emotional contagion based on the above conditions. We have learned that the negative emotional value of the agent i is mainly related to their personality parameter u_i, which represents the urgency of an individual. The agent's negative emotions should increase as time pass if the value of u_i is high. Therefore, we define the negative emotion due to the urgency of oneself as follows in Equation (2):

$$e_u(i,t) = e_u(i,t-1) + u_i t^{\partial}, \tag{2}$$

where i is the order number of the agent, t is the time parameter, ∂ represents the time index. Equation (2) shows that the negative emotional value e_u of urgency will increase exponentially with time.

3.2 Other individual impacts on emotional value

In the queuing scenario, in addition to their own factors, the influence of other events on the individual emotional value should be considered, such as the behavior of queue jumpers and the emotions of other individuals. Therefore, we need to address the problem of emotion-related effects and contagion among individuals.

The most widely used model of emotion contagion is the SIR model [31]. This model divides the population into three categories: susceptible(S), infected(I), and removal(R). The susceptible person has not acquired the disease but lacks immunity and is easily infected after contacting the patient. Furthermore, the infected person refers to the infected person and can be transmitted to a susceptible person. In addition, a removal person is quarantined or immunized for the disease. In this model, individuals can interact with others and respond to their perceived emotions. This model reflects the macroscopic mechanism of emotional contagions [49]. Because the original SIR model is static, it may not be suitable for describing people with abnormal emotions, especially those in line. Therefore, the model should be modified to be microscopic and dynamic to reflect the emotional contagion in crowd queuing simulation.

In the queuing scenario, the agent's negative emotions are affected not only by its urgency value but also by other events, such as the queue-jumping phenomenon and other agents' negative emotions. The approach here to calculate negative emotions is inspired by the model of emotional infection in reference [21]. When queue jumping occurs, we define the negative emotion of agent i under the effect of queue jumper j as follows in Equation (3):

$$D_{ji} = [1 - \frac{1}{(1 + exp(-L))}] \times E_i \times A_{ji} \times B_{ij}, \tag{3}$$

where L represents the distance between individuals i and j. E_i represents the emotional expression intensity of individual i, which takes values in the range of $(0, 1)$. The closer to 1, the stronger the individual's extroversion, the stronger the emotion expressed outwardly, and vice versa. A_{ji} represents the emotional intensity attribute given by interloper j to individual i, which is related to the individual's extroversion. B_{ij} represents the intensity attribute of the emotion received from the emotion individual i back to the emotion sender j; this attribute is related to the empathy of the receiving individual.

3.3 Emotional combination

We fuse the two negative emotion values of the agent to calculate the negative emotion value (e_{neg}) of individual i at time t, as shown in Equation (4).

$$e_{neg}(i, t) = e_u(i, t) + \sum_{j=1}^{K} D_{ji}, \tag{4}$$

where K represents the number of queue jumpers within the perception range of agent i.

3.4 Emotional outburst

This section presents an emotional outburst model in the queuing scenario. In psychology, an emotional outburst has many meanings, including all intensities and hundreds of causes, such as anxiety, fear, anger, or worry. However, no matter how different the causes and results, emotional outbursts have some common attributes: rapid, complex, interactive, repeated, and predictable.

In the SIR model, we define the probability of emotional outbursts based on the concept of susceptible and infected individuals. In addition, we study the relationship between the agent's patience and the length of time, which is introduced by Mandelbaum and Zeltyn [41]. Therefore, we define the emotional outburst as follows in Equation (5):

$$p = \begin{cases} 0, & e_{\text{neg}} > 0.5 \\ 1 - e^{-\tau u_i \Delta t}, & e_{\text{neg}} < 0.5 \& \Delta t < w_i \\ 1, & e_{\text{neg}} < 0.5 \& \Delta t \geq w_i \end{cases} \tag{5}$$

where Δt represents waiting time.

Equation (5) shows that when the final value of negative emotion is greater than 0.5, the probability of an emotional outburst is 0. When the agent is in a negative state, waiting time Δt does not reach the individual's patience value w_i, and the emotional outburst will be higher if the urgency u_i of agent i is higher and the waiting time is longer. In addition, the probability of an emotional outburst will be 1 if the waiting time in the queue is longer and reaches the individual's patience value w_i.

3.5 Individual location update

In normal queuing, the new agent always moves to the last position of the queue. However, when the negative emotions burst, the agent will jump in line and move to the front of the queue. The agent's queue jumping location depends on the intensity of negative emotion. We need to define a rule that considers the debilitating process of negative emotions and how to choose where to cut in line after an emotional outburst.

In this section, we will define the intensity of negative emotions by Hooke's law. Hooke's law is one of the fundamental laws in the theory of elasticity. It states that the force f needed to extend or compress a spring by some distance l scales linearly concerning that distance. That is, $f = kl$, where k is a constant factor characteristic of the spring. In physics, the energy conservation law states that an isolated system's total energy remains constant. Therefore, when the spring length is changed, the elastic potential energy will be transformed into kinetic energy, and when the spring length returns to a normal length, the elastic potential energy will be zero. H.J. Eysenck [18] applies Hooke's law to calculating individual emotional values. Emotions can be the driving force of individual behaviors. Therefore, we can consider the individual's negative emotion of individual i at time t as the elastic potential energy f of the spring, as shown in Equation (6):

$$e_{neg}(i,t) = -kl, \tag{6}$$

where k is the variation coefficient of the negative emotion value, and l is the walking distance of the individual.

We assume that the individual movement rules are as follows:

- Queue jumping in this queue, the movement rule of the individual is to get out of the queue first and then move in the direction between the individual and the service point.
- If the queue jumper is not in the queue, it moves directly in the direction between the individual and the service point.

After calculating the moving distance of the queue jumper by Equation (6), the individual will move toward the front of the queue. When the individual with the burst of negative emotions reaches the target location, the individual moving distance is l at this time. The individual will search for the position in front of the agent with the highest friendliness f_i within a specific range of the point to cut the queue. When moving from the target location to the queue-cutting position, the movement distance of the individual is α. So from emotional outbursts to successful queue jumping, the total distance an individual walks is $l + \alpha$. When the queue jump is successful, the individual's positive and negative emotions are updated, and we define the change of emotion in Equation (7) as follows.

$$\begin{cases} e_{pos} = 0.5 + k\alpha, \\ e_{neg} = 1 - e_{pos}. \end{cases} \tag{7}$$

3.6 Emotional control with administrator

Queue jumping may lead to crowd press and even more severe accidents in the queuing scenes. The most commonly used method to prevent crowd disorder is to assign administrators. Administrators can effectively reduce the spread of negative emotions in the crowd and stabilize individual behaviour with negative emotions.

An administrator is equivalent to a positive emotional source, which can suppress an individual's negative emotions and strengthen positive emotions. In other words, the administrator can effectively reduce the diffusion of negative emotions of the crowd and eventually stabilize the crowd's emotions.

Supposing the administrator's positive sentiment is e_a, and the positive emotional value of an agent within the administrator's perception is e_{pos}. We define the increment of the agent's positive emotion value Δe_p under the role of administrator as follows in Equation (8):

$$\Delta e_p = \frac{e_a - e_{pos}}{e_a + e_{pos}}. \tag{8}$$

When the positive emotions of the administrator are higher than the individual, the administrator's role can be reflected. Therefore, we assume $e_a \geq e_{pos}$. By Equation (8), we can see that when the difference in the positive emotional value between the individual and the administrator is large, the positive emotional value of the individual increases more. This shows that administrators pay more attention to individuals with low positive emotions and control the diffusion of negative emotions in the crowd by managing the negative individuals.

4 MODELING AGENT BEHAVIOR

In the queuing scenes, the behaviours of each agent are different. Many factors affect the behaviour of the agent, including the factors of the agent itself: character, emotion, patience, urgency, and vision range; also include the factors of the external environment: obstacles, the behaviours, and emotions of other agents.

As shown in Figure 1, agents can sense the external environment and get information about other agents, queues, obstacles, and service points through interaction with external environment parameters. Then we calculate the behaviour and path of the agent by the emotional infection model proposed.

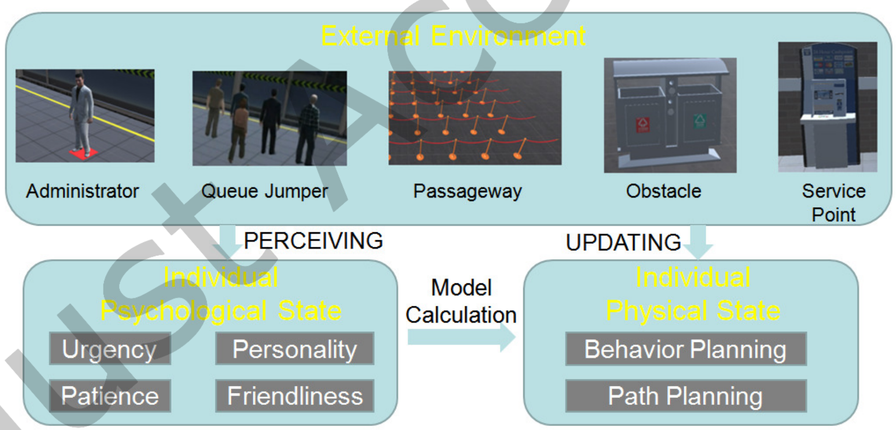


Fig. 1. Behavioral modeling.

Figure 2 details the algorithm of agent behaviour calculation, which includes four modules: external environment parameters, model calculation, behaviour decision, and path planning. The agent first calculates the emotional impact D_{ij} of other agents from the information extracted from the external environment. Then, the negative emotion values e_{neg} of the agent are updated by the external environment parameters and their personality factors (urgency u_i, friendliness f_i, patience w_i). Next, we judge whether the agent's negative emotions will erupt. The agent will remain in the queue if the emotions do not erupt. If the emotions erupt and no administrator is on the scene, the agent will jump in the queue. If an administrator is on the scene, calculate the administrator's impact on the emotions.

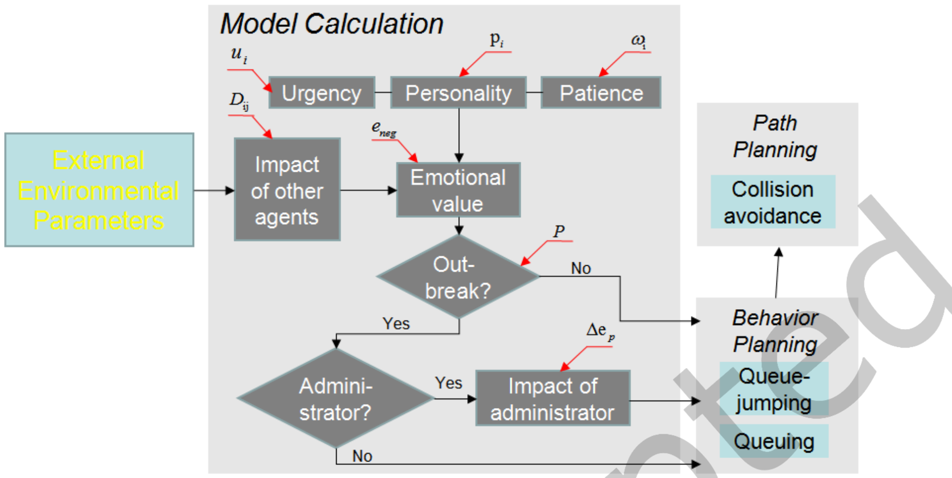


Fig. 2. The mechanism of agent queuing. The algorithm logic of the Figure 1 module is described in detail. It consists of four modules: external environment parameters, model calculation, behaviour planning, and path planning. The red arrow represents model parameters.

We use cellular automaton to simulate the states of individuals. Each agent can only move to the adjacent cell in each time step. If more than one agent chooses the same cell as the next moving target, we will rank them according to their emotional intensity so that the agent with a high negative emotional value has the priority of choosing a location.

In the simulation process, an individual has six possible states, q_1, q_2, q_3, q_4, q_5, and q_6, representing non-queuing, queuing, queue-jumping, waiting for service, receiving service, and ending service states, respectively. The relationship between these states is shown in Figure 3. When the agent enters the scene, it is in q_1 state. When the emotional value of the agent is updated, if the queue-jumping condition is not triggered, the agent will walk to the last position of the queue and maintain q_2 state; otherwise, the agent walks forward and maintains q_3 state. When the agent enters the queue, he/she waits for service and remains in q_4 state. q_3 and q_4 can be converted into each other. When the agent arrives at the service point to accept the service, he/she remains in q_5 state. Finally, the agent ends the service and leaves the scene, moving to q_6 state.

5 EXPERIMENTS AND RESULTS

We construct five crowd queue simulation scenarios to validate our method. In the experiments, we used the hardware environment: i7 processor with 2.8GhZ, GTX 1070 graphics card, and 16g RAM. The software environment used is MATLAB r2019a, Visual Studio 2019. For better visualization and analysis, we use the Unity3D tool to visualize and analyze various states of the agent.

5.1 Experimental scenario setup and analysis

To verify the effectiveness and applicability of our method, we tested the proposed method from different perspectives using five typical queuing scenarios: ATM, subway station, bus station, indoor service windows and outdoor service windows.

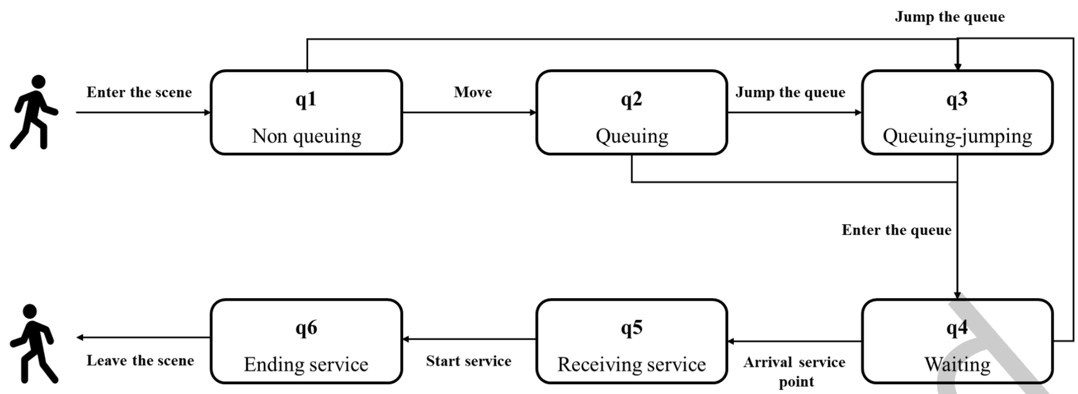


Fig. 3. The diagram of queuing state transitions.

Below we analyze the characteristics of these queuing scenarios:

- **ATM**: The ATM scenario is a common one-to-one service queue scenario where an ATM can only provide service to one customer at a time. A long queue will be formed if many customers come quickly.
- **Subway Station**: The subway station has many subway doors, and passengers have many options. Generally, passengers will look for a waiting area with the fewest people to queue.
- **Bus Station**: The bus station scenario is a common queuing scenario. In this scenario, people waiting for the bus are always eager to get on, creating congestion.
- **Indoor Service Window**: Indoor service window scenes always have a barrier to control the crowd in line. Therefore, individuals cannot cross the fence to cut the line, effectively preventing crowd confusion.
- **Outdoor Service Window**: Outdoor service window scenes do not always have a barrier to control the queue, so the queue is prone to chaos.

All presented scenarios generally have two necessary modules: agents and buildings. Three agent modules were created for the agents: young, old, and children. The building and obstacle modules are simulated based on real scenes to make the animation more realistic.

In the experimental section, we will present four of these scenarios in detail and compare and analyze the simulation experiments from different perspectives:

1) Comparison between the proposed model with and without emotion contagion: We conduct comparison experiments between the proposed model and without emotion contagion in the ATM queuing scenario.

2) Comparison with the traditional crowd model simulation method: We conducted comparison experiments between the proposed model and a cellular automata-based model of emotional contagion [21] in the subway scenario.

3) Comparison with the actual scenario: We conducted experiments with the proposed model in an indoor service window (with a fence) scenario and an outdoor service window (without a fence) with a real queueing scenario, where the real-world data is sourced from our collection of web queueing videos.

4) Comparison with administrator intervention at different times: subway station scenario.

5.2 Experimental parameter setting

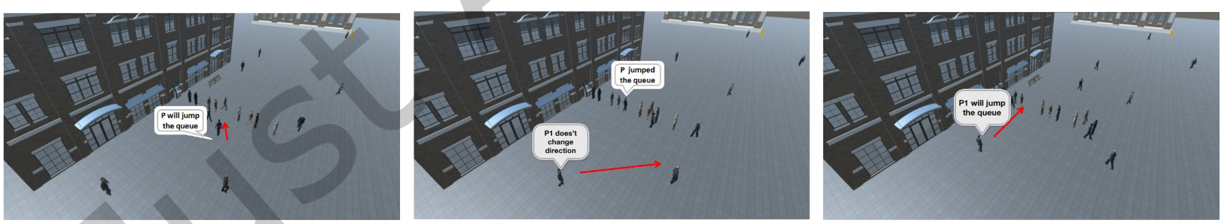
We conducted a series of experiments in various scenarios using different models. The number of agents and the values of the parameters taken in different scenarios are shown in Table 1. w_i, u_i, and f_i are taken randomly using the Gaussian distribution N(0,0.25) [16]. The movement speed of the agent is 0.8, the perception range of the agent is 10 m, and the time index $\partial = 1.2$. The values of these parameters were finally obtained by continuous comparison of the simulation results and the actual results using the method in reference [56].

Table 1. The value of the simulation scene parameters

Scene	Model	Agent Number	Scene Size
ATM	The model without emotional infection	20	800×1000
ATM	Our model	20	800×1000
Subway	Cellular automata[21]	42	1200×800
Subway	Our model	42	1200×800
Indoor service window (with a fence)	Our model	26	1000×1000
Outdoor service window (without a fence)	Our model	30	1000×1000

5.3 Comparison between the proposed model with and without emotion contagion

In the ATM scenario, this section gives the operation of individuals without emotional contagion and with emotional contagion. There are two modules in the ATM scenario: the crowd and the service point module. We first simulate the crowd movement trend under the no-emotion contagion model. Only individual emotion values and basic queuing rules are considered, without considering factors such as interactions between individuals and individual personalities. Then the crowd movement trends are simulated under the emotion contagion model proposed.



(a) Initial motion state. (b) Under the model without emotional contagion. (c) Under our model.

Fig. 4. ATM simulation scene diagram. (a) Individual P about to insert. (b) Individual P_1 is inserted at the end of the queue. (c) Individual P_1 is inserted into the queue.

Figure 4a depicts the ATM scene in the initial crowd movement state. In the experiments, parameters such as the emotional infection model and personality were not added. At the initial state, an interloper P was added, whose movement direction was the idle position in front of the queue, while the queuer P_1 movement direction was the back of the queue. The final experimental results are shown in Figure 4b. The agent P_1 does not change its walking direction and continues to move toward the tail of the queue after the queue-jumper P completes the queue-jumping. When the new emotional infection model proposed is added to the scene, the crowd movement trend is shown in Figure 4c. The agent P_1 changes its walking direction and moves toward the front of the queue after the interloper P completes the interjection and makes the interjection.

5.4 Comparison experiments with the traditional emotional infection model

Due to the unique nature of the subway station scene, three scene modules are set up for the experiment in this subsection: the crowd module, the obstacle module, and the waiting area module in front of the subway entry/exit door. The waiting area module includes a crowd waiting in front of the subway entry and exit doors. The subway crowd queuing form is different from the typical queuing scenario. The crowd queues up on both sides of the waiting area by the subway doors. These conditions are sufficient for queue jumpers, who, due to emotional outbursts, choose to wait in the queue in the lane where the crowd gets off.

Under the traditional situation infection model, this section first simulates crowd movement in the subway scene. The initial state of crowd movement is shown in Figure 5a, from which it can be seen that, unlike the common queuing scenario, the crowd begins to form a queue on both sides of the subway entry and exit doors.

(a) Initial motion state. (b) Under the traditional emotional contagion model. (c) Under our emotional contagion.

Fig. 5. Subway station simulation scene diagram. (a) The crowd begins to line up. (b) The crowd forms two normal queues under the traditional emotional infection model. (c) The crowd forms a four-row abnormal queue under our emotional contagion.

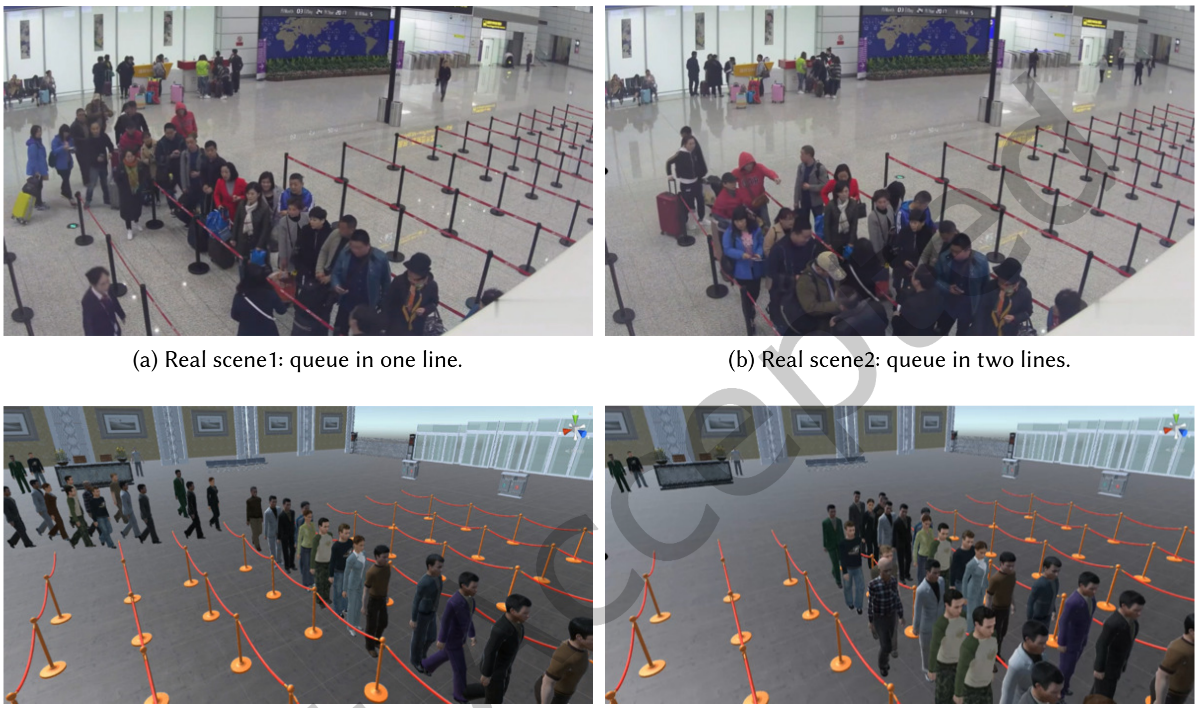
The simulation results without adding the new emotion model are shown in Figure 5b. Crowds are arranged in an orderly manner in the waiting area, forming a normal left-right queue form. When the number of people in this waiting area increases, other people who are about to enter the queue will choose other waiting areas in the entry and exit doors to wait.

We simulated the movement trend of the crowd in the subway with an emotional infection model, as shown in Figure 5c. After adding the emotion infection model, the emotional value of an individual will trigger the queue insertion condition, and the crowd will move forward to form a new irregular queue. Other individuals also jump the queue after their emotions are affected, and eventually, four queues are formed in the waiting area. After the number of individuals in that waiting area increases, the rest of the crowd moves to the area with fewer individuals in the waiting area.

5.5 Comparison experiments with real scenarios

Two experimental scenarios are presented to verify the practicality of the emotional infection model proposed: indoor service window and outdoor service window. We compare the simulation results with the realistic indoor and outdoor service window scenarios.

5.5.1 Indoor scenes. The special feature of the indoor service window scenario is that the crowd cannot directly insert itself into the existing queue. Due to administrators and barriers, the crowd always gathered at the end of the queue. When the crowding level reaches a certain level, the crowd forms a new queue at another service window under the arrangement of the administrator, as shown in Figures 6a and 6b. We set the constraints in the algorithm according to the actual scenario. When the crowding level at the end of the queue reaches a specific condition, a new service point is opened so that the crowd can form a new queue at this new service point, as shown in the simulation results in Figures 6c and 6d.



(a) Real scene1: queue in one line.

(b) Real scene2: queue in two lines.

(c) Simulation scene1: queue in one line.

(d) Simulation scene2: queue in two lines.

Fig. 6. Comparison of indoor service window scenes with real scenes. (a) is the state in which no new queue is formed, and (b) is the state in which a new queue is formed after the number of queue members reaches a certain level; (c) and (d) are the corresponding model simulation scenario.

5.5.2 Outdoor scenes. Unlike the indoor window service scenario, there is no fence and only one service window in the outdoor scenario. When many people approach the service window, the crowd gathers in front of the queue without the barrier, slowly generating congestion, as shown in Figures 7a and 7b. We base on the specificity of the scenario that when the number of people behind the queue reaches a certain level, individuals gather around the service window, which leads to congestion. Figures 7c and 7d show the simulation results.

5.6 Comparison experiments with different time interventions of administrators

This paper aims to prevent chaos at the queue site, and the most effective measure is to send administrators to manage the crowd on time. Individuals with negative emotions tend to be stable under the influence of administrators. The administrator can keep the order of the crowded queue and eliminate the spread of negative

(a) Real scene1: queue in normally state.

(b) Real scene2: queue in abnormally state.

(c) Simulation scene1: queue in normally state.

(d) Simulation scene2: queue in abnormally state.

Fig. 7. Comparison of outdoor service window simulation and real scenario. (a) is the state when the queue is not chaotic, and (b) is the state when chaos is formed in the queue after the emotional value of the crowd reaches a certain level; (c) and (d) are the corresponding model simulation scenario.

emotions. This summary experiment observes and analyzes the change in crowd movement by simulating a subway scene and by controlling the timing of the administrator's appearance.

Figure 8a and Figure 8b show that two administrators appear in the scene but at different times, and the red circle represents the perceived range of the administrator. In Figure 8a, this paper sets two fixed positions in the subway scene, and the administrator will appear in these two positions in advance when the crowd has not yet been infected with negative emotions. As seen from the figure, within the range perceived and managed by the administrator, i.e., in the red area, the orderly crowd lines up in two queues in the waiting area, and no queue jumping occurs.

In Figure 8b, the administrator appears after the crowd's negative emotions spread. Two fixed points are set in the experiment so that the administrator walks to the fixed point from the left side at a certain speed. The figure shows that the queueing area becomes chaotic when the crowd's negative emotion spreads. Then the administrator appears from the left side and walks to the designated position. During the administrator's march, some crowds still jumped the queue because they were not within the administrator's range of action. Still, when the administrator gradually approached the fixed point, and the waiting area entered the administrator's range of action, the subsequent crowds appearing in the subway scene began to queue in order. The phenomenon of chaos in front of the queue in the waiting area and order in the back appeared.

(a) Administrator early intervention.

(b) Administrator intervention after a disruption.

Fig. 8. Simulation scenario diagram of administrator intervention. (a) The queue remains normal. (b) The queue goes from chaotic to normal.

6 DISCUSSION AND ANALYSIS

6.1 Overview

We aim to propose a personality-based model of emotional contagion and control in crowd queuing simulations by integrating individual emotions. We conducted simulation experiments in Unity3D to verify the effectiveness of the model, the scientific validity, and the proposed management solution. Using psychological and social computing, we first proposed individual emotional parameters (patience, urgency, and friendliness). Then we added the dynamic parameters to the SIR model and combined them with a cellular automata model to construct a crowd emotional infection simulation model. Finally, we added administrators to the model to control the crowd disorder in the queue. Through extensive experiments, we show that our proposed model can reasonably, realistically, and effectively simulate various queueing scenarios; the appropriate addition of queueing channels and the introduction of administrators can suppress crowd disorder in queues.

6.2 Analysis and discussion of results

In this subsection, we analyze and discuss the results of the four comparison experiments in Section5. The details are given as follows.

- **Comparison between the proposed model with and without emotion contagion**

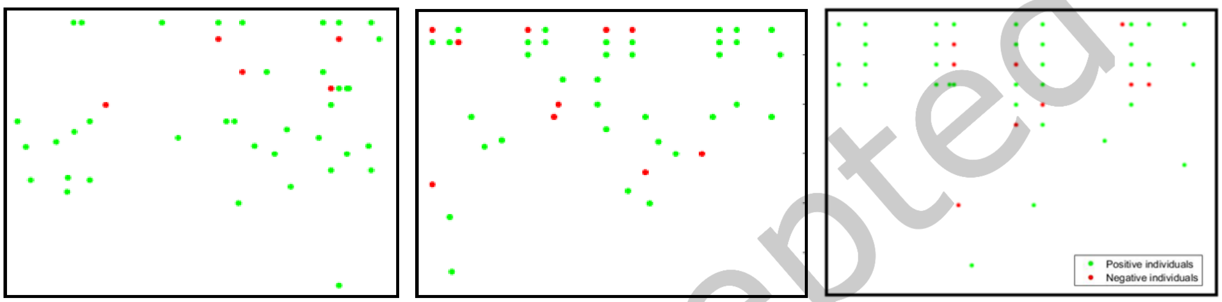
  Based on the experimental results, we can analyze that in the normal simulation model without the emotional infection model, the crowd in the queue queues generally in the case of other individuals inserting into the queue, i.e., the crowd's behaviour in the queue does not affect each other. In our model simulation, individuals in the queue will be infected by others in the case of queue jumping. They will join the queue-jumping, i.e., the behaviour of the whole queue will affect each other.

  Compared with the model without emotional infection, the simulation results of our model are more similar to the realistic scenario. This experiment can justify the inclusion of emotional parameters in our method.
- **Comparison experiments with the traditional emotional infection model**

  We use a user study to analyze our proposed model in this subsection. The user study uses the same simulation scenarios and parameter settings in the comparison experiments. It mainly compares three contagion degree, chaos degree, and realism degree metrics in the simulation results. We define these three indicators as follows.

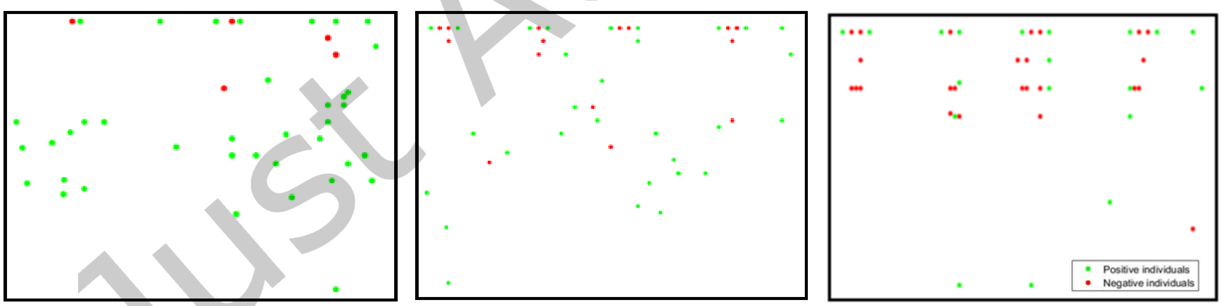
(1) Contagion degree: the increased rate of people infected by emotions at the final state can reflect the contagion rate of negative emotions in the queue.
(2) Chaos degree: the increased rate of the number of queues at the final state, which can reflect the impact of negative emotions on the queueing order.
(3) Realism degree: similarity between the simulation results and the actual scenario.

To compare the differences between the two models more intuitively, we collected and analyzed the crowd emotions in the subway scene. We selected the crowd's emotional values at the initial, intermediate, and final moments. We represented the distribution of the positive and negative emotion crowd with a scatter plot, as shown in Figures 9 and 10.



(a) Initial moments (b) Intermediate moments (c) Final moments

Fig. 9. Distribution of positive and negative agents in the traditional model. The green color represents positive individuals, and the red color represents negative individuals. The figure's top and bottom are the queue's head and tail, respectively.



(a) Initial moments (b) Intermediate moments (c) Final moments

Fig. 10. Distribution of positive and negative agents in our model. The green color represents positive individuals, and the red color represents negative individuals. The figure's top and bottom are the queue's head and tail, respectively.

To compare the apparent differences between the two models more precisely, we analyzed the data variation of the user study in the subway scene by data statistics. The details are shown in table 2. Where $T_{Im}, N_{Im}, P_{Im}, Q_{Im}$, denote the total number of individuals, the number of negative individuals, the number of positive individuals, and the number of queues at the initial moment. $T_{Fm}, N_{Fm}, P_{Fm}, Q_{Fm}$ denote the total number of individuals, the number of negative individuals, the number of positive individuals, and the number of queues at the final moment. $Contagion_{Ir}$ denotes the rate of increase of negative emotional individuals, and $Queue_{Ir}$ denotes the rate of increase in the queue.

Table 2. Comparison of user study data

Model	T_{Im}	N_{Im}	P_{Im}	Q_{Im}	T_{Fm}	N_{Fm}	P_{Fm}	Q_{Fm}	$Contagion_{Ir}$	$Queue_{Ir}$
Traditional model	42	5	37	8	44	9	35	10	8.6%	25%
Our Model	42	5	37	9	43	25	19	16	46.2%	77.8%

Figures 9, 10, and Table 2 show that the total number of individuals, negative individuals, positive individuals, and queues are similar in the initial stages of both models. However, in the intermediate and final moments, our model differs significantly from the traditional model.

First, given the contagion degree, the traditional model had 9 negative emotional individuals at the final state, and the emotional contagion growth rate was 8.6%. Our model had 25 negative emotional individuals at the final state and an emotional growth rate of 46.2%. In contrast, negative individuals in our model spread faster and more widely.

Second, given the chaos degree, the traditional model has 10 queues at the final state, 2 more than the initial state, with a queue growth rate of 25%. Our model has 16 queues in the final state, which is 7 queues more than the initial state, and the queue growth rate is 77.8%. In addition, the newly added queues are all in the passenger drop-off area, which has a more chaotic impact on the overall queuing environment. In contrast to the traditional model, individuals in our model who are affected by emotional contagion are more reluctant to obey the queueing order and cause more chaos.

(a) (b) (c) (d)

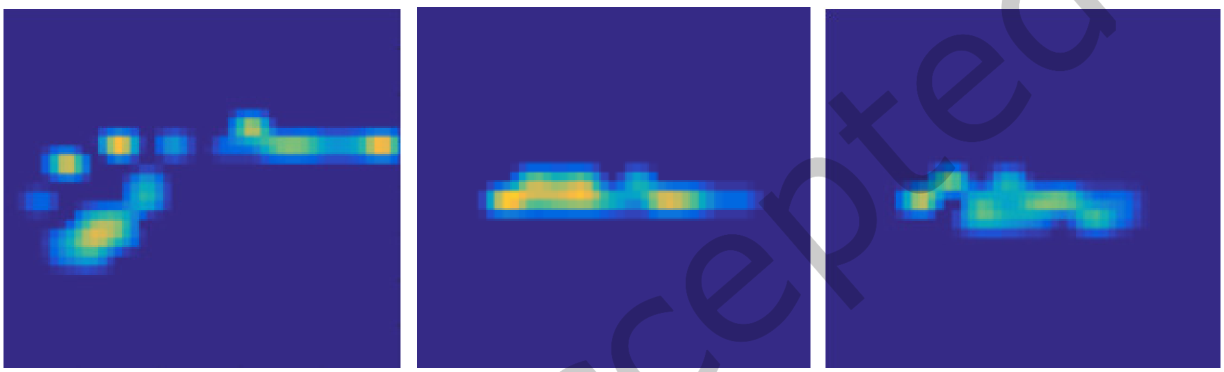
Fig. 11. Real subway queuing scene. The green dashed arrows in the figure are the waiting area queues, and the red dashed arrows are the non-waiting area queues.

Finally, we collected the subway waiting queue scenario to compare it with the model simulation results, as shown in Figure 11. In the actual scene, when queue jumping and chaos occur in the queue, the queuing scene is more similar to the effect of our model simulation, which is more in line with the real subway scene.

- **Comparison experiments with real scenarios**

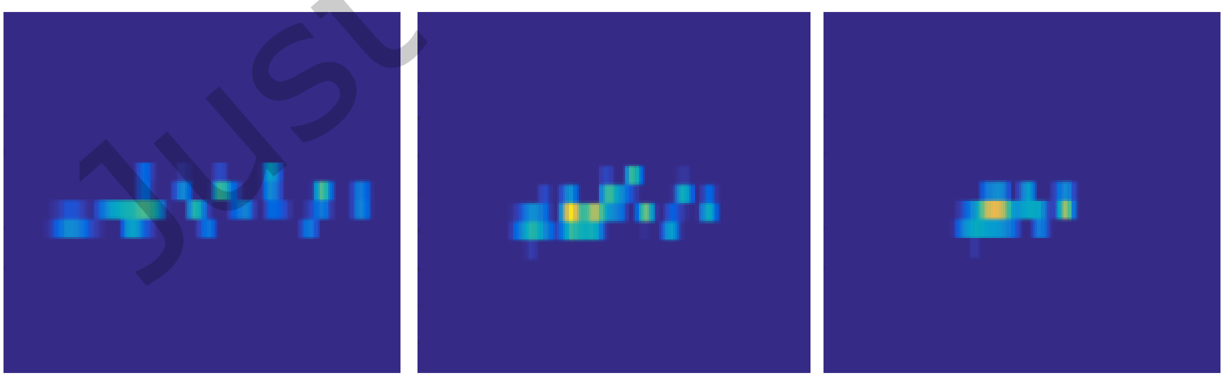
  In this summary, we still conduct a user study on the proposed model. The actual scenario is used as a comparison in that experiment. A similar simulation scenario is used in this user study, mainly to compare the distribution of the crowd emotion and the realism degree in the simulation results.

Figures 9 and 10 classify individuals as negative and positive based on their sentiment values, which only reflect the individual at a given moment. However, individual sentiment value is a range, and the value change needs to be processed. To highlight the overall change process in the emotional value of the crowd in the queue. We visualize the emotion values derived from the experiment in a heat map, as shown in Figures 12 and 13. The sentiment heat map analyzes which part of the queue is more chaotic and the degree of chaos in the queue. Each graph represents the distribution of the sentiment values of the crowd in the scenario at 1, 10, and 20 seconds. In Figures 12 and 13, the blue areas represent positive sentiment values; the brighter the color, the higher the positive sentiment value. Yellow areas represent negative sentiment values; the brighter the color, the higher the negative sentiment value. The dark blue color is the background of the figure.



(a) 1s (b) 10s (c) 20s

Fig. 12. Emotional heat map of the indoor window scene. The figure shows the top view of the queue, where the right side is the head of the queue, and the left side is the tail of the queue.



(a) 1s (b) 10s (c) 20s

Fig. 13. Emotional heat map of the Outdoor window scene. The figure shows the top view of the queue, where the right side is the head of the queue, and the left side is the tail of the queue.

To more accurately compare the model's performance in different scenarios, we present the distribution of the population sentiment values in the cohort during the experiment. The details are shown in Table 3. Where N_{1s}, P_{1s}, N_{10s}, P_{10s}, N_{20s}, and P_{20s} denote the distribution of negative and positive emotions in individuals at the 1st, 10th, and 20th seconds. We use D_1, D_2, D_3 to denote the distribution with the larger the number, the denser the population. The number of the crowd is denoted by A_1, A_2, A_3, and the larger the number, the more individuals there are.

Table 3. Crowd Emotion Distribution

Scene	N_{1s}	P_{1s}	N_{10s}	P_{10s}	N_{20s}	P_{20s}
Indoor	D_1, A_2	D_1, A_2	D_1, A_3	D_1, A_1	D_1, A_1	D_2, A_2
Outdoor	D_1, A_1	D_1, A_3	D_2, A_2	D_2, A_2	D_3, A_3	D_1, A_1

Combined with Figures 12, 13, and Table 3, it can be seen that: there are significant differences in the distribution of emotions in the crowd under different scenarios and queuing rules.

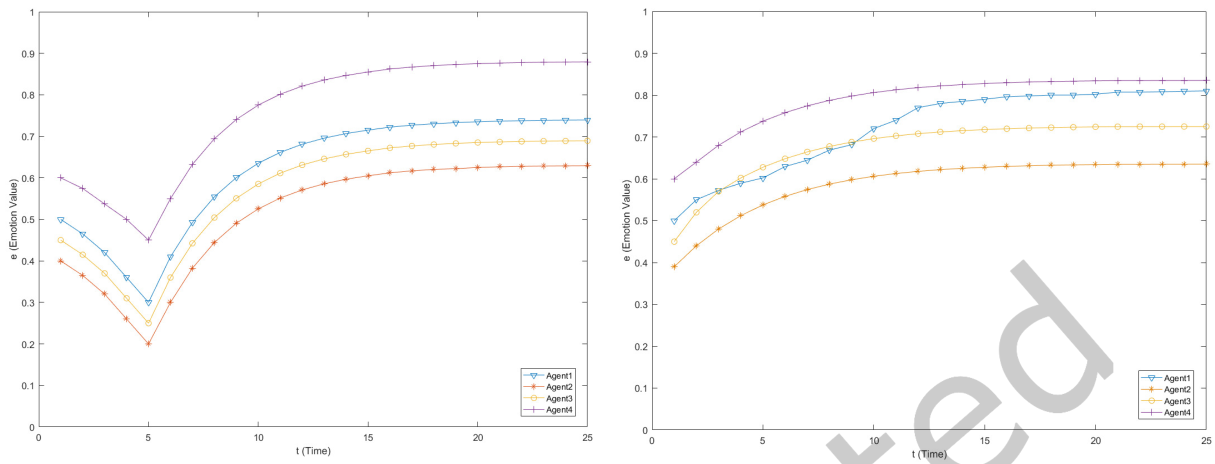
In the indoor scenario, there were barriers on both sides of the queue to separate the queues. From Figure 12, it is found that: in the 1st second, the number of queues is one, and negative and positive emotions individuals are scattered in all parts of the queue, but the negative emotion at the end of the queue is more concentrated. In the 10th second, after adding a new service window, the queue turned into two teams. The queue head turns to positive emotions, while the negative emotions at the end of the queue start to spread to the middle. On the 20th, as the service proceeded, the queue began to move forward normally, and the negative emotions slowly disappeared.

In the outdoor scenario, the queue was free of obstacles. From Figure 13: In the first second, individuals were scattered in the queue, and no obvious queue was formed. Positive emotions dominated individuals' emotions, and many negative emotions existed in the latter part of the queue. At the 10th second, individuals began to concentrate, and the queue length shortened, forming a chaotic situation. In the latter part of the crowd, individuals changed to negative emotions. At the 20th second, the crowd gathered, causing the queue to disappear, and the scene became more chaotic. Negative emotions were evenly distributed in the crowd.

Finally, we found that our model's indoor and outdoor simulation processes are similar to the scenarios shown in Figures 6a, 6b, 7a and 7b. Our method can detect and prevent congestion in specific queuing scenarios, which is of great practical value for managers to control the queuing situation and resource scheduling in the area. This experiment also verifies the practicality of our method.

- **Comparison experiments with different time interventions of administrators**

Through experiments 5.3, 5.4, and 5.5, we found that individual negative emotions significantly impact the queue structure. For this reason, we introduced administrators in experiment 5.6 to suppress the transmission of individuals' negative emotions. To get a more accurate understanding of the effect of introducing administrators, we select the experimental data (individual emotion values) of individuals in the four cohorts in the scenario and analyze the trend of personal emotion changes of these individuals under the intervention of the administrator at different periods, as shown in Figure 14a and Figure 14b. Figure 14a represents the administrator's intervention before the negative emotional outburst in the cohort, and Figure 14b represents the administrator's intervention after the negative emotional outburst in the cohort.



(a) Administrator intervention after a disruption.

(b) Administrator early intervention.

Fig. 14. Trends in individual emotion values in the two cases. (a) The emotional change trend when the administrator appears after negative emotions spread. (b) The emotional change trend when the administrator appears before negative emotions spread.

The graph shows that when the administrator intervenes before the negative emotion erupts, the individual's emotional value keeps increasing under the administrator's action (the more significant the emotion value means, the more positive emotion). When the negative emotion appears to spread, and the act of queue jumping occurs, at this time, no administrator appears, and the individual's emotion value keeps decreasing (the lower value represents the more serious negative emotion). When the administrator appears at t=5, the individual's emotion value changes from a decreasing trend to an increasing trend, the individual's negative emotion gradually decreases, and finally, the individual reaches a positive state and maintains a stable level.

From the experimental analysis, we can conclude that the administrator's presence positively affects queue disorder, and the earlier the administrator intervenes, the earlier the queue enters an orderly state. This experiment also verifies the necessity of introducing administrators to our model.

6.3 Research significance

Our proposed model can simulate various common queuing scenarios according to our definition. In other scenarios with similar queuing rules, our model can also be a simulated model, such as a bus queuing scenario, nucleic acid testing queuing scenario, and stadium ticket checking queuing scenario. In addition, our model can be extended to group simulation to provide a theoretical basis for large-scale group simulation. Our model has a specific promotion value in such scenarios. It has certain scientific research value, such as studying humans in biology and psychology, multi-agent systems, computer graphics and other cross-research fields of many disciplines. It has certain societal values such as security control, building layout planning, and game and movie characteristics. With the introduction of administrators in the model, we give reasonable and scientific suggestions for the management problems existing in the queuing scenario, such as increasing queue lanes, service windows, and on-site managers. Our model is helpful for managers in deploying resources, maintaining crowd order, and improving queuing quality.

7 CONCLUSIONS

Based on summarizing the existing crowd simulation models, we analyze the importance of the emotional infection model. From the perspective of psychology and social computing, we establish an effective emotional infection model of individual personality and friendliness based on personality, patience, urgency, and friendliness to represent the emotional parameters. In addition, we propose an administrator's emotion model to prevent confusion in the queuing crowd. The contributions of this paper are highlighted as follows:

- Integrating the influence of individual mentalities and interpersonal relationships, we present a computational model of emotional contagion and control for queuing crowd simulations. The model includes some emotional parameters such as patience, urgency, and friendliness that effectively represent individual personality based on the SIR model. Hooke's law also calculates the weakening of individual negative emotions in queuing events.
- In addition, we propose an administrator role to control the crowd's emotional infection and maintain the order of the queue. The experimental results show that our method can inhibit the spread of negative emotions in the crowd and enhance positive emotions, preventing crowd chaos in the queue.

The simulation of crowd queuing behaviour based on the analysis of emotional contagion is a challenging research topic involving many subjects, such as computer science and psychology. Although our model can provide a solution for crowd management in common queuing scenarios. However, in reality, managing chaotic crowds can exceed the assumptions in our model. Such as some cases where the crowd is out of control and does not obey the administrator's arrangement or even resists, these problems are worth further study. In future work, we will deepen the present research by combining computer vision techniques and an efficient method of crowd aggregation computation in public areas [57] to collect crowd movement parameters, consider some extreme cases and add a variable speed mechanism to the model to improve further the emotional contagion analysis and modelling of crowd queue events.

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